ICIS 2019 Proceedings | Analytics and Data Science

Different Prices for Different Customers – Optimising Individualised Prices in Online Stores by Artificial Intelligence

Alper Be?er
Technische Universität Dortmund, alper.beser@tu-dortmund.de

Richard Lackes
Technische Universität Dortmund, Richard.Lackes@TU-Dortmund.de

Markus Siepermann
Technische Universität Dortmund, markus.siepermann@tu-dortmund.de

Different Prices for Different Customers – Optimising Individualised Prices in Online Stores by Artificial Intelligence

Completed Research Paper

Alper Beşer
Technische Universität Dortmund
44221 Dortmund, Germany
alper.beser@tu-dortmund.de

Richard Lackes
Technische Universität Dortmund
44221 Dortmund, Germany
richard.lackes@tu-dortmund.de

Markus Siepermann
Technische Universität Dortmund
44221 Dortmund, Germany
markus.siepermann@tu-dortmund.de

Abstract

Today's information tracking technology and Big Data open up new opportunities for e-commerce. Online stores can collect personal information to estimate customers' willingness-to-pay. This enables the application of price differentiation where different customers are charged different prices for the same product. Lower prices offered to customers who share the word have an advertisement effect, while higher prices have adverse effects. In this paper we develop a decision model for individualised prices in online stores that considers the sharing of prices by word of mouth which is mostly neglected by current literature. Complex decision models in e-commerce are caught between the need of adequately representing the reality and the demand of being solvable within reasonable time limits. We use various artificial intelligence solution methods to solve the decision model for numerical examples. Our results indicate that despite word of mouth differential pricing can be financially worthwhile.

Keywords: Personalised pricing, price differentiation, price discrimination, electronic word of mouth, reference price effects

Introduction

With recent years' improvements and increased use of information tracking technology, firms are becoming more capable of gathering behavioural information about their customers (Chen and Chen 2015; Aydin and Ziya 2009; Liu and Zhang 2006). The data collected in this way can be used to create accurate profiles that help to understand the needs of customers (Thakur et al. 2011). This process is facilitated by the large amounts of data generated in the age of Big Data. Accurate customer-related information enables firms to price discriminate between their customers such that different customers are charged different prices for the same product or service (Chen and Chen 2015; Bourreau et al. 2017; Aloysius et al. 2009; Krämer et al. 2018). Firms apply price discrimination in order to maximise their profit (Bourreau et al. 2017; Ghose et al. 2002). The term price discrimination has no negative connotation and is synonymous with price differentiation (Phlips 1983). Research on consumer welfare indicates that customers may profit from differential pricing as well (Bourreau et al. 2017; Richards et al. 2016). With price differentiation firms can provide affordable prices to customers with lower purchasing power who otherwise would not be able to afford the good. In general, price discrimination is divided into three categories: first-degree (personalised pricing), second-degree (volume discounts or bundling), and third-degree (group pricing) price discrimination (Bourreau et al. 2017; Chang and Yuan 2007; Varian 1989; Pigou 1920). Personalised pricing is applied when customers are offered tailored prices depending on individually available information (Aydin and Ziya 2009, Shapiro et al. 1998). Personalised pricing is referred to as perfect price discrimination if customers are charged exactly their willingness-to-pay (Varian 1989) which is defined as the maximum amount of money a customer is willing to spend on a product or service (Wertenbroch and Skiera 2002). Third- and second-degree price discrimination are already widely adopted in the real world (e.g. student discounts or bundle pricing), but there is a trend towards personalised pricing (Bourreau et al. 2017; Chen and Chen 2017). While volume discounts or bundling require the least amount of information, the adoption of group and personalised pricing is characterised by a significantly higher requirement for customer data (Bourreau et al. 2017). For a precise estimation of the customers' willingness-to-pay, accurate customer profiles are needed. These consist of two parts: (1) the *static customer profile* based on static, long-term oriented personal data such as gender, age, or income and (2) the *dynamic customer profile* based on dynamic data concerning the short-term behaviour of customers in online stores including visit frequency/history, total visit duration, shopping cart analysis data etc. (Thakur et al. 2011; Niu et al. 2002). The more data a firm collects about its customers, the higher is the estimation accuracy of the willingness-to-pay and the more individualised are the prices offered to customers. However, the application of such pricing strategies also involves risks. A substantive problem of price discrimination and the resulting price heterogeneity concerns the low customer acceptance. A customer or a group of customers may feel disadvantaged by being offered higher prices (Xia et al. 2004). In the age of social media and electronic word of mouth (WOM) information spread faster and can reach a substantially higher level of network dissemination (Mochalova and Nanopoulos 2014; Pfeffer et al. 2014; Cannarella and Piccioni 2008). A high level of price transparency regarding other customers being privileged in terms of prices can lead to perceived price unfairness. Numerous incidents in the past have shown that first-degree price discrimination can initiate large waves of customer complaints. As an infamous example, in 2000 Amazon had been widely criticised by its customers for selling a DVD at different prices depending on whether cookie information was available for a visiting customer (Enos 2000; Bourreau et al. 2017). Recent developments have also shown that the acceptance of pricing based on collected data among customers is still low when it was revealed that Amazon changed prices up to 300 times during a few days (Hirsch 2015). As a result, WOM and the resulting price transparency on the market should be considered as a risk factor in the entrepreneurial profit maximising pricing decision. Derived from these opportunities and risks, we investigate the following research questions (RQ):

RQ1*: How should a decision model for price differentiation be formalised that considers customer data and word of mouth effects?*

RQ2*: Is artificial intelligence suitable for finding adequate solutions to complex pricing decisions?*

Concerning the first research question RQ1, we develop a decision model for offering individualised prices in online stores. The model's theoretical underpinning is based on findings from relevant theoretical and empirical literature. An appropriate pricing decision model is required to comprise the multifaceted inter-dependencies between the store's decision variables and the customer reaction behaviour. The resulting complexity of such models usually prevents analytical solutions for practical problem sizes. For numerical analyses, powerful solution methods are needed as found in the research field of artificial intelligence (AI). Therefore, as an answer to the second research question RQ2 we propose the use of an evolution strategy. To test the power and applicability of this method, we solve the developed decision model numerically for exemplary scenarios under realistic conditions as WOM is incorporated in our model. For assessing the quality of the results generated by the evolution strategy, we benchmark them against the results of other AI and non-AI solution methods. Thus, from a practitioner's point of view, this paper contributes to the development and application of practical individualised pricing strategies in e-commerce. Only a few studies have examined the effects of WOM in the relevant price discrimination literature (see next section). Most of these studies consider the sharing of product information but neglect that price information can also be passed by WOM. In our study, customers can get informed about prices offered to both directly and indirectly connected market participants and may react to price discrepancies and disadvantageous price discrimination, i.e. perceived price unfairness, in different ways. Thereby, this paper also contributes to price discrimination literature by providing insights into when WOM may harm a firm's profit and when it may be beneficial in the presence of individualised prices.

The remainder of this paper is organised as follows. The next section gives an overview of related literature. In section 3 we introduce our decision model that is solved in section 4 for numerical examples by various solution methods. The examined examples include various price discrimination strategies that are compared to uniform pricing. In section 5 a summary of the results is given, from which managerial implications are drawn. The section closes with limitations and future research directions.

Related Literature

In our approach, the prices of the seller will vary depending on a visiting customer's static attributes and his/her dynamic behaviour leading to a heterogeneous price situation on the market. This paper is therefore closely related to the research on reference price effects which is a sub-stream of price discrimination literature. Reference prices are formed by customers based on market observations and experiences (Koschate-Fischer and Wüllner 2017). Customers use reference prices as an anchor point to evaluate offered prices (Kalyanaram and Little 1994; Hu et al. 2016). Hu et al. (2016) examine a monopoly setting where customers' reference prices are based on past prices that are exponentially smoothed depending on a memory factor. The customers are strategic and profit seeking. The authors could show that a cyclic pricing policy is optimal for a myopic pricing strategy, where the seller only seeks to maximise the profits in the current period without planning strategically for future periods. The model of Hu et al. (2016) among others considers reference prices to be the same for all customers in each period (e.g. Popescu and Wu 2007; Fibich et al. 2003; Greenleaf 1995; Kopalle et al. 1996). Wang (2016) uses heterogeneous reference prices in his model that enables different reference prices on an individual level. Wang (2016) also considers a monopolistic market setting where different groups of customers have heterogeneous arrival schedules. Each customer has a reference price that is based on exponentially smoothed prices that were offered to him on previous visits. The results suggest that more frequently visiting customers should be charged higher prices to keep their willingness-to-pay high for later periods. On the contrary, for less frequently visiting customers it is optimal to extract the momentarily available surplus by offering lower prices. Our work is closely related to Wang (2016), but contrary to the model of Wang (2016) we do not limit the updating of the reference prices to store visits. Customers are able to obtain new information about the prices offered to other customers outside the store by WOM. Hence, we distinguish between internal and external reference prices. The latter is formed from information obtained from observing the market. Another key distinction is that the visiting schedule is not fixed per group, but changes on an individual level. Non-buying customers may decide on their next visit based on the difference between the observed prices and their willingness-to-pay.

This paper is also related to price discrimination literature that incorporates WOM effects. In this stream of literature several papers have examined the optimal pricing strategy in a network of interconnected individuals. Most studies price discriminate based on network centrality measures and show that influential customers with a greater number of peers or with a more centralised position in the network should be offered lower prices (e.g. Bloch and Quérou 2013; Campbell 2008; Candogan et al. 2012; Chen et al. 2018; Fainmesser and Galeotti 2015). The discounts incentivise customers to engage in WOM by informing other customers of the availability of the purchasable good. Communicating with directly linked neighbours and all network participants are referred to as local and global network externalities respectively. Most of these studies implicitly assume that WOM has a solely positive effect on the firm's profit by informing other customers about the product's existence or quality. Because of this their research objective is often related to increasing the level of WOM in the network. The studies do not consider that WOM can be financially harmful as it may also be used for passing information about prices except for Bloch and Quérou (2013) who allow the sharing of prices only in the direct neighbourhood. It is conceivable that price information itself is sufficient to change the demand by either attracting customers to visiting the store or by dissuading them from doing so. Different prices for the same good may also lead to perceived price unfairness as mentioned in the introduction section. In Bloch and Quérou's (2013) model, customers form their reference prices depending on the surrounding price offers and gain a positive utility if they get charged lower prices than their peers. The authors could show for a monopolistic setting that customers with a high degree centrality should be offered higher prices for increasing the overall demand in the network. However, the authors do not take into account that in the age of electronic word of mouth a customer may also get informed about the prices of distant, indirectly linked network participants. In the authors' model the customer similarity is not considered either which might entail customers' acceptance for others paying less. A frequent feature of papers in this stream of price discrimination literature is their game theoretical approach. Most of the abovementioned studies use a two-staged game where at first the seller sets a price and then all market participants simultaneously decide whether to purchase the product. This causes challenges for adequately modelling WOM and its dynamics. If all customers decide on purchasing a product at the same time, the time-dependent information dissemination and its effects in the network are not sufficiently taken into account. To address this, in our model the customers act independently of one another in terms of store visits, product purchases, and sharing of prices via WOM.

Author(s)	Objective	Degree of Price Discrimination	Market Setting	Customer Communication (Word of Mouth)	Findings
Bloch and Quérou 2013	effects of node centrality on optimal discriminatory prices	first-degree	monopoly, oligopoly	customers have knowledge about the product consumption and prices in their local neighbourhood	• a monopolist should charge higher prices to influential customers (hubs) if customers compare prices via WOM in their neighbourhood • in directed graphs prices are higher for customers who are more susceptible for influence
Campbell 2008	optimal pricing strategies in a random network	first-degree	monopoly	customers tell their peers about the existence of the product depending on their valuation and the offered price; lower prices lead to more WOM	• customers with a greater number of peers should be offered lower prices to increase the level of WOM
Candogan et al. 2012	optimal pricing strategies in social networks	first-degree	monopoly	customers pass information on the product's quality to their local neighbourhood	• the more influence a customer has, the greater is the discount • authors provide an algorithm for finding an optimal set of customers who should get a discount
Chen et al. 2018	optimal pricing strategies in social networks that are varied in density	first-degree	monopoly, duopoly	customers have knowledge about the product consumptions in their local neighbourhood	• in a monopoly more WOM always benefits the seller in terms of profits and prices • in a duopoly WOM has opposing effects; although more WOM increases demand, it also leads to intense competition between competitors leading to lower prices
Fainmesser and Galeotti 2015	optimal pricing strategy and its effects on consumer surplus if seller uses information about customers' susceptibility (in-degree) and influence (out-degree) in the network	first-degree	monopoly	customers know about the consumption of the product in their local neighbourhood and whole network	• the seller should offer discounts to influential customers in the network to initiate WOM and charge the susceptible customers higher prices
Kamada and Öry 2017	optimal contracting (bundling) in a social network with referral interaction among customers	second-degree	monopoly	customers only send referrals to other customers if their expected utility is greater than their opportunity costs	• to increase the level of WOM, the seller should offer free product features to customers who would otherwise not make a purchase
Gramstad 2016	optimal contracting (bundling) in a social network where the seller has no knowledge about its structure	second-degree	monopoly	customers know about the consumption of the product in their local neighbourhood	• a share of the customers should be offered prices below the seller's marginal costs in order to increase the level of WOM leading to greater overall profits

Table 1. Related price discrimination studies that incorporate word of mouth effects

Model

Specifying the Pricing Decision Problem

To decide on individualised prices and their consequences we consider an online store setting where a seller (hereafter referred to as *she*) offers a durable good over a finite time horizon $t = 1, \ldots, T$. A customer (hereafter referred to as *he*) is denoted by $i = 1, \ldots, I$. Let $b_{it} \in \{0,1\}$ denote if customer i purchases the product at time step t for the individualised price p_{it}, $0 < p_{it}$, that is offered to him on a store visit. Then, the objective function of the seller can be formulated as a maximisation problem of her total profit Π where the marginal costs for each sold product unit are denoted by c, $0 \leq c < p_{it}$:

$$\text{Maximise } \Pi = \sum_{t=1}^{T} \sum_{i=1}^{I} (p_{it} - c) \cdot b_{it} \tag{1}$$

The maximisation has to be done subject to the following conditions. The seller assigns all visiting customers to a customer group $g = 1, \dots, G$ where g_i shall describe customer i's group. We assume that the seller has collected and evaluated enough information to classify her customers in regard to their characteristics, e.g. by using decision trees or artificial neural networks (Shim et al. 2012). Although these groups are disjoint, they exhibit a certain degree of similarity to each other which may result from similar customer-specific attributes such as age or income. For this, let s_{gh}, $0 \leq s_{gh} \leq 1$, denote the similarity between two groups g and h with $s_{gh} = s_{hg}$. The group allocation is based on static customer attributes and therefore constitutes the static customer profile. A group g has W subgroups to which its arriving customers are dynamically allocated to depending on the number of their previous visits that are tracked by the seller. Thus, the subgroup allocation forms the dynamic customer profile. For all possible profile combinations of groups and visits that can occur in the two-stage profile allocation process the model needs to provide a specific price. These prices depict the seller's decision variables and are summarised in the price matrix $PM \in \mathbb{R}_{+}^{GxW}$. The greater the dimensions of PM are, the greater is the degree of price discrimination. The price element pm_{gw} represents the price that will be offered to a member of the group g on his wth visit where $w = 1, \dots, W$ with $W \leq T$, meaning that regardless of when a customer visits the store for the first time, he will be offered the 1st price of his group g (i.e. pm_{g1}). If he has visited the store more than W times, for any forthcoming visit he will be offered the Wth price (i.e. pm_{gW}). Two distinct customers belonging to the same group can get offered different prices while simultaneously visiting the store because of differences in their visit history. Note that for $W = 1$ and $G = 1$ there is no price discrimination since all customers are offered the same price. For $G = I$ the pricing strategy equals personalised pricing where each customer has his own group that has W individualised prices. Consequently, $1 < G < I$ describes group pricing. Each customer is described by his time-dependent willingness-to-pay WTP_{it}, $0 \leq WTP_{it}$. The random visiting behaviour of customers is modelled on an individual level and follows a discrete distribution. On average, all customers visit the store every λ, $1 \leq \lambda$, time steps. Investigations regarding customer retention in online stores have shown that prices are the predominant factor in the customers' choice of online retailers (Reibstein 2002). Hence, online stores use low prices in an attempt to attract new customers (Schmitz and Latzer 2002). From this we deduce that the individual duration until a customer's next store visit, denoted by λ_{it}, $1 \leq \lambda_{it}$, depends on the difference between the customer's WTP_{it} and his price expectations influenced by the offered price. For smaller differences he may return sooner anticipating an early buying opportunity, whereas large differences might frighten him off from revisiting the store again. On a store visit, a customer's group assignment and former visiting behaviour determines the price that will be offered to him. In this context, let $v_{it} \in \{0,1\}$ indicate if a potential customer i is visiting the store at time step t. Based on his group membership and the number of his earlier visits the offered price p_{it} is defined as:

$$p_{it} = pm_{g_i w_{it}} \;, \quad w_{it} = min\left\{W, \sum_{\tau=1}^{t} v_{i\tau}\right\} \;, \quad \forall i \in \{1, \dots, I : v_{it} = 1\} \tag{2}$$

At time step t a visiting customer i purchases the product only if his willingness-to-pay WTP_{it} is greater than or equal to the offered price p_{it}. However, some researchers suggest that the willingness-to-pay of a customer is not a fixed point, but rather a range (see Schlereth et al. (2012) for an overview). Because this range may vary between customers, we incorporate this into our model as an individually generated random parameter $\tilde{\varepsilon}_{it}$, $0 \leq \tilde{\varepsilon}_{it} \;\; \forall i \in \{1, \dots, I : v_{it} = 1\}$, that shall represent customer i's flexibility towards small differences between p_{it} and WTP_{it} on a purchase occasion. This means, even if $p_{it} > WTP_{it}$ the customer might still purchase the product if the difference is sufficiently low, i.e. $p_{it} - WTP_{it} \leq \tilde{\varepsilon}_{it}$. After making a purchase, the customer will not return to the store, such that $\sum_{\tau=t+1}^{T} v_{i\tau} = 0$. Based on this, the purchase decision of customer i who visits the store at time step t can be described as:

$$b_{it} = \begin{cases} 1 & if \quad p_{it} \leq WTP_{it} + \tilde{\varepsilon}_{it} \\ 0 & else \end{cases} \;, \quad \forall i \in \{1, \dots, I : v_{it} = 1\} \tag{3}$$

Customers outside the store are not able to purchase the product: $b_{it} = 0 \;\; \forall i \in \{1, \dots, I : v_{it} = 0\}$.

Willingness-To-Pay Adaptation and Word of Mouth Effects

The willingness-to-pay of a customer is not a fixed parameter and may change over time where WTP_{i0}, $0 < WTP_{i0}$, depicts a customer's exogenously predetermined initial willingness-to-pay:

$$WTP_{it} = WTP_{it-1} + \Delta WTP_{it-1} \ , \quad \Delta WTP_{i0} = 0 \tag{4}$$

When evaluating potential changes to their willingness-to-pay, customers are oriented to so-called reference prices (Koschate-Fischer and Wüllner 2017; Johnson and Cui 2013; Grunert et al. 2009). Reference prices are used by customers to judge the fairness of offered prices (Johnson and Cui 2013; Winer 1986). A reference price RP_{it} forms a customer's price expectations (Mazumdar et al. 2005) and causes his WTP_{it} to either increase or decrease (Koschate-Fischer and Wüllner 2017; Johnson and Cui 2013). Empirical evidence for the reference price oriented adjustment of the willingness-to-pay is provided by Grunert et al. (2009). In our proposed concept for the modification of the willingness-to-pay, the incremental change ΔWTP_{it} depicts the amount of adaptation of WTP_{it} towards RP_{it}. Each customer is characterised by an upper limit for his willingness-to-pay until which he agrees to make changes to it: $WTP_{it+1} \leq WTP_i^{upper\,limit}$. In total, a customer may only change his willingness-to-pay n times. A customer's number of modifications that took place before time step t is denoted by n_{it}. We define two cases for triggering a potential modification of the willingness-to-pay that differ with regard to whether a customer is inside or outside the store: (1) the customer visits the store and declines an offer and (2) the customer observes other prices on the market when activated by WOM. For this, let $k_{it} \in \{0,1\}$ indicate if customer i is being activated by WOM and knows about at least one other price at time step t. If neither case (1) nor (2) occurs or if the customer has already surpassed the modification limit, there will be no modification of the willingness-to-pay: $\Delta WTP_{it} = 0 \ \ \forall i \in \{1, \dots, I: (v_{it} = 0 \wedge k_{it} = 0) \vee n_{it} \geq n\}$. If case (1) or (2) occurs, the amount by which the willingness-to-pay WTP_{it} changes depends on its difference to the reference price RP_{it}. Grunert et al. (2009) provide evidence that the willingness-to-pay linearly increases towards a higher reference price. For a lower reference price we assume that the willingness-to-pay will likewise decrease linearly. However, customers attach different weights to economic gains and losses according to the prospect theory of Kahneman and Tversky (1979). If the customer increases his WTP_{it}, he will pay more than initially intended, which can be seen as an economic loss (Johnson and Cui 2013; Mazumdar et al. 2005). In the converse case, the customer pays less than originally planned, which is perceived as an economic gain (Johnson and Cui 2013; Mazumdar et al. 2005). Due to the customers' loss aversion (Mazumdar et al. 2005) it is inferable that a customer will decrease his WTP_{it} considerably faster than increasing it. We therefore define the slope of the linear decrease to be greater. The coefficients α and β denote the slope of the linear decrease and increase respectively. For $\alpha = 1$ or $\beta = 1$ the customer will immediately adapt his WTP_{it} to RP_{it}. We define the difference $\alpha - \beta$ as the degree of loss aversion. The parameter ϕ is a threshold value for the increasing case. If the customer's price expectations denoted by RP_{it} are considerably higher than his current WTP_{it} (i.e. $\phi < RP_{it} - WTP_{it}$), we assume that he will not increase his WTP_{it} at all.

$$\Delta WTP_{it} = \begin{cases} \alpha \cdot (RP_{it} - WTP_{it}) & if \qquad RP_{it} - WTP_{it} \leq 0 \\ \beta \cdot (RP_{it} - WTP_{it}) & if \quad 0 < RP_{it} - WTP_{it} \leq \phi \\ 0 & if \quad \phi < RP_{it} - WTP_{it} \end{cases}, \tag{5}$$
$$0 < \phi, \quad 0 \leq \beta < \alpha \leq 1, \quad \forall i \in \{1, \dots, I: (v_{it} = 1 \vee k_{it} = 1) \wedge n_{it} < n\}$$

Reference prices can be differentiated into internal and external reference prices (Hu et al. 2016; Liu and Zhang 2006; McCarville et al. 1993). The internal reference price IRP_{it} reflects a customer's memories for prices from past or current purchase occasions (Johnson and Cui 2013; Mazumdar et al. 2005). The external reference price ERP_{it} usually refers to price information that is available externally (Mazumdar et al. 2005). It depicts a regular or base price that a product is usually sold at (Koschate-Fischer and Wüllner 2017; Kopalle and Lindsey-Mullikin 2003; Krishna et al. 2002).

The internal reference price IRP_{it} of a customer gets updated when he visits the store. Research concerning reference prices is not unequivocal. Some papers use all offered prices and exponentially smooth them when calculating IRP_{it} (e.g. Hu et al. 2016; Wang 2016). Others argue that there is a lack of substantial evidence for exponentially smoothed average prices in behavioural research (Koschate-Fischer and Wüllner 2017; Nasiry and Popescu 2011) and that customers are unlikely to remember past offerings well except for the very last purchase situation (Krishnamurthi and Phillips 1992). We follow the former and exponentially smooth the internal reference price IRP_{it} that gets updated when the customer visits the store. The smoothing factor $\psi_i \in [0,1]$ is modelled on an individual level and determines a customer's memory for price offerings in the past. The parameter ψ_i is also called assimilation parameter that determines a customer's sensitivity to differences between the newly offered price p_{it} and the old internal reference price IRP_{it-1} (Mazumdar et al. 2005). For $\psi_i = 1$ a customer only remembers the very last price offered to him (Wang 2016) or, in other words, completely assimilates new prices (Mazumdar et al. 2005). Let $av_{it} \in \{0,1\}$ denote if customer i has already visited the store at least once until time step t. If the customer visits the store for the first time at time step t, his internal reference price will equal the offered price: $IRP_{it} = p_{it}$. On successive visits the IRP_{it} will be updated in the following way:

$$IRP_{it} = \begin{cases} IRP_{it-1} & if \quad v_{it} = 0 \\ IRP_{it-1} + \psi_i \cdot (p_{it} - IRP_{t-1}) & if \quad v_{it} = 1 \end{cases}, \quad t \geq 2, \quad \forall i \in \{1, \dots, I: av_{it} = 1\} \tag{6}$$

In our model, the external reference price ERP_{it} is based on the prices that customer i observes on the market at a given time step t. A customer is only aware of prices offered to other customers in the network if they have been passed to him by WOM. For this, let $m_{ijt} \in \{0,1\}$ denote if customer i has received price information from customer j at time step t, i.e. if he knows about the price p_{jt} paid by the customer j at the same time step ($b_{jt} = 1$). Furthermore, let $ak_{it} \in \{0,1\}$ denote if customer i has already been activated by WOM at least once until time step t.

According to the theory of social comparison, customers focus more on the prices paid by customers who are in a comparable situation (Bloch and Quérou 2013). It is conceivable that to some extent people accept price differences for certain groups like students or retired people. In analogy to the above-defined assimilation parameter, a customer's old ERP_{it-1} should change depending on the similarity to the sender from whom he has obtained price information. More (less) similar customers have a greater (smaller) influence on the formation of his updated external reference price ERP_{it}. To put it differently, the receiver i's similarity $s_{g_i g_j}$ to a sender j determines the degree of assimilation of the sender's price. We assume that the interaction between customer i and j suffices for an adequate assessment of the mutual similarity. In case of multiple received prices, the average of all similarity-weighted price differences will be used for updating his external reference price. If the obtained prices are from highly dissimilar customers, the external reference price will hardly be modified. If a customer gets activated by WOM for the first time, his external reference price will correspond to the average of the prices known to him: $ERP_{it} = (\sum_{j \in \{1,\dots,I\} \setminus i} m_{ijt} \cdot p_{jt}) / (\sum_{j \in \{1,\dots,I\} \setminus i} m_{ijt})$. Afterwards, we define the updating of ERP_{it} as:

$$ERP_{it} = \begin{cases} ERP_{it-1} & if \quad k_{it} = 0 \\ ERP_{it-1} + \dfrac{\sum_{j \in \{1,\dots,I\} \setminus i} m_{ijt} \cdot s_{g_i g_j} \cdot (p_{jt} - ERP_{it-1})}{\sum_{j \in \{1,\dots,I\} \setminus i} m_{ijt}} & if \quad k_{it} = 1 \end{cases}, \\ t \geq 2, \quad \forall i \in \{1, \dots, I: ak_{it} = 1\} \tag{7}$$

The actual reference price RP_{it}, to which the customer adapts his WTP_{it} to, is based on the internal and external reference price. IRP_{it} and ERP_{it} are known to the customer as soon as he has visited the store or has been activated by WOM respectively. If both conditions are met, the customer is aware of both reference prices. In this case, the relative weight between both reference prices is determined by the customer's price sensitivity (Koschate-Fischer and Wüllner 2017; Mazumdar et al. 2005; Krishnan et al. 2013; Murthi et al. 2012; Moon et al. 2006) that shall be denoted by η, $0 \leq \eta \leq 1$. Highly price sensitive customers ($\eta \to 1$) will mainly look at the prices that others pay when defining their reference price. Customers are more likely to make a purchase if they personally benefit from discriminatory pricing (Richards et al. 2016). We therefore assume that the price sensitivity η only plays a role if other customers pay less (i.e. $IRP_{it} > ERP_{it}$). If the customer is privileged or at least equally served in his perception of prices (i.e. $IRP_{it} \leq ERP_{it}$), he will pick his internal reference price as RP_{it} which will make an increase of his WTP_{it} and thereby a purchase more likely.

$$RP_{it} = \begin{cases} WTP_{it} & if \quad av_{it} = 0 \quad \wedge \quad ak_{it} = 0 \\ ERP_{it} & if \quad av_{it} = 0 \quad \wedge \quad ak_{it} = 1 \\ IRP_{it} & if \quad av_{it} = 1 \quad \wedge \quad ak_{it} = 0 \\ IRP_{it} & if \quad av_{it} = 1 \quad \wedge \quad ak_{it} = 1 \quad \wedge \quad IRP_{it} \leq ERP_{it} \\ \eta \cdot ERP_{it} + (1 - \eta) \cdot IRP_{it} & if \quad av_{it} = 1 \quad \wedge \quad ak_{it} = 1 \quad \wedge \quad IRP_{it} > ERP_{it} \end{cases} \tag{8}$$

Model Solution

Applied Solution Methods

The proposed decision model describes in a formalised way the profit caused by the seller's pricing decision depicted in the price matrix $PM \in \mathbb{R}_+^{GxW}$. The determination of the optimal elements of the price matrix is complex because of the profound interdependencies and the model's stochastic variables that for example concern the customers' store visiting and purchase behaviour. Therefore, an analytical solution cannot be implemented for practical problem sizes. To provide numerical solutions to pricing decisions that today's online stores are confronted with, we propose the deployment of an evolution strategy as an artificial intelligence solution method often used for continuous optimisation problems (Emmerich et al. 2018). We benchmark it against other AI methods (simulated annealing and particle swarm optimisation) and non-AI methods (greedy algorithm and Monte Carlo simulation). Evolution strategies are based on an analogy to biological processes of genetic selection of the best suited features. Starting with a set of individuals (population) that are characterised by their genetic attributes, subsets are chosen to simulate a reproduction procedure for generating new individuals and testing their fitness (Emmerich et al. 2018). To implement an evolution strategy for our decision problem, first an operationalisation of an individual is needed. Because an individual represents a possible solution to our pricing decision model, it can be constructed as a matrix of the dimensions GxW containing positive numerical values depicting the prices of the seller. The fitness of an individual is determined by the profit it generates in a given scenario. In order to obtain representative fitness values in a stochastic environment, the simulation of an individual's financial outcome needs to be conducted multiple times. Second, the genetic processes of generating new individuals and determining the survival conditions in the transition to the next generation need to be defined. The evolution strategy (ES) was conducted as ($\mu^{ES} + \lambda^{ES}$)-ES where μ^{ES} denotes the number of parental individuals in each generation. By various mutation and recombination methods the parents are used to generate children whose number is represented by λ^{ES}.We parameterised the evolution strategy with $\mu^{ES} = 10$ parents where each parent generated multiple children by mutating its elements with a step size of $\sigma^{ES} = 5$. To reduce the risk of getting trapped in a local optimum, additional children were generated by recombining randomly selected parents. To enrich the population with good genes, a "kindergarten" was added where three randomly created individuals were protected for five generations. In total, $\lambda^{ES} = 139$ children were generated in each generation whose fitness was calculated according to equation (1). For all scenarios the evolution strategy was stopped after 100 generations. Afterwards the best-performing individual among the survivors was identified representing the found solution to the seller's decision problem. The particle swarm optimisation mimics animal swarm behaviour found in nature such as the movement of birds. Animals belonging to the swarm are in the optimisation process represented by so-called particles denoting possible solutions that move around in the problem's solution space. The velocity of each particle's movement depends on the previous velocity, the personally found best position in the solution space, and the global best position identified by the swarm. (Bonyadi et al. 2014) Simulated annealing is based on the metallurgical annealing process and has the advantage of being able to leave local optima. Depending on a decreasing temperature level that determines the step size and the currently known best solution, a trial solution is generated and evaluated. If it performs better, it is henceforth defined as the best known solution. In the converse case, it may still be defined as the so far best-performing solution with a given probability that decreases with the temperature. (Dowsland et al. 2012) As a non-AI solution method a greedy algorithm was tested where the prices of a possible solution were consecutively optimised. We also performed a Monte Carlo simulation where potential solutions were randomly generated. The solutions of all tested methods were evaluated according to their fitness. To improve the quality of the found solutions, scenario-adjusted lower and upper boundaries were defined for the solution space. To achieve performance comparability, each solution method was granted approximately the same simulation time as the evolution strategy. The statistics for the best found solutions were calculated by re-conducting their fitness calculation 1.000 times. The profits generated by these solutions provide the basis for the numerical analysis.

Parameterisation and Scenario Development

To examine the performance of the solution method and to analyse different scenarios we modelled and solved a numeric example for an exemplary online store. Some of the parameters constituting the numerical example were fixed and others were varied for carrying out a sensitivity analysis. The former include, for instance, a fixed time horizon of $T = 100$ and the customer segmentation. We define three different customer groups A, B, and C that represent the store's customer segment structure. We normalised the number of potential buyers to 100 where 10% belong to group A, 20% to group B, and 70% to group C. The customer groups are denoted by the indices $g \in \{1,\ 2,\ 3\}$. Each group g has a similarity of $s_{gg} = 1$ to itself. The group of A customers has a similarity of $s_{12} = s_{21} = 0.5$ and $s_{13} = s_{31} = 0.1$ to the groups of B and C customers respectively. The groups of B and C customers have a similarity of $s_{23} = s_{32} = 0.5$ to each other. The customers of group A represent the seller's most loyal customers and have a significantly higher initial willingness-to-pay WTP_{i0}. To generate WTP_{i0} we introduce a market price level $pl = 100$ that can be interpreted as a scaling factor and is used for defining boundaries $[0, 3 \cdot pl]$ for the decision problem's solution space. The values for A customers are drawn from a normal distribution with an expected value of $\mu(WTP_{i0}) = 2 \cdot pl$. Customers of group B have a considerably lower willingness-to-pay with $\mu(WTP_{i0}) = 1.25 \cdot pl$. The least loyal customers belong to group C with $\mu(WTP_{i0}) = pl$. For all groups the standard deviation is $\sigma(WTP_{i0}) = 5$. The upper limit of the customers is fixed at $WTP_i^{upper\ limit} = 1.1 \cdot WTP_{i0}$. The smoothing factor is set to $\psi_i = 0.9$ so that new offered prices are quickly adopted as internal reference prices by the customers. The marginal costs for each sold product are $c = 0$. The flexibility parameter $\tilde{\varepsilon}_{it}$ for small differences between the offered price and the customer's willingness-to-pay is drawn from a right-sided triangular distribution between 0 and 3. This makes a purchase more likely if the offered price is greater than the willingness-to-pay only by a small amount. The greater the difference is, the less likely the customer will make a purchase. Furthermore, we chose $\phi = 0.5 \cdot pl$ so that the difference between WTP_{it} and RP_{it} has to be less than 50 in order to initiate an increase of WTP_{it}. The price sensitivity was set to $\eta = 0.8$ inducing customers to have a low tolerance for similar customers paying less.

The set of varied model parameters comprises the customer visit frequency, loss aversion, and price transparency on the market resulting from word of mouth. To test different visit frequencies, the base level for the expected duration until the next store visit is varied: $\lambda \in \{1,\ 5,\ 20\}$. For instance, $\lambda = 20$ represents a low visit frequency and means that without modification of the customer arrival times (i.e. $\lambda_{it} = \lambda$) each customer would visit the store every 20 time steps. The expected duration λ_{it} is modified depending on the weighted difference between the reference price and willingness-to-pay. As a weighting factor we chose 0.5, meaning that a customer with an encountered difference of $RP_{it} - WTP_{it} = 10$ will increase his expected duration λ_{it} until the next store visit by $10 \cdot 0.5 = 5$ time steps. For generating the actual random durations a discrete geometric distribution is used. In the following, we will refer to the visit frequency scenarios as high visit frequency (HF), medium visit frequency (MF), and low visit frequency (LF). To test various degrees of loss aversion, we set the increasing adaptation speed of the willingness-to-pay to $\beta = 0.1$ and varied the decreasing speed $\alpha \in \{0.2,\ 0.5,\ 1\}$. Greater values of α lead to higher degrees of loss aversion where customers reduce their willingness-to-pay faster upon observing cheaper prices. These three cases will be called low loss aversion (LLA), medium loss aversion (MLA), and high loss aversion (HLA). In order to examine the effects of different price transparency levels, an operationalisation of the binary WOM reception indicator m_{ijt} is needed. For mimicking a real social network environment for the store's customers, we developed an analogous WOM model comprising the customer interaction in the following way. Real social networks are characterised by clustered areas in which the customers are highly connected to each other and so-called bridges or weak ties that represent connections between the clusters leading to a faster information dissemination in the network (Onnela et al. 2007; Cowan and Jonard 2004). An artificial network that shares these characteristics is the small world network model of Watts and Strogatz (1998). For creating small world networks, we used $I = 1000$ as the number of vertices in the graph, $lp = 10$ as the lattice parameter, and a rewiring probability of $r = 0.1$. Messages omitted in social networks are subject to decay depending on a half-life (Nugroho et al. 2015) that determines the distance δ it reaches in the network. We define the distance as the longest possible walk originating from the sender vertex. For $\delta = 1$ a sender would only reach his directly connected neighbours, whereas for $\delta = 2$ his second-degree neighbours would be informed, too and so forth. Messages with a high half-life have a low distance because they quickly lose their topicality and thereby reach only a small fraction of the network and vice versa. We define $\omega \in [0.1]$ as the edge pass-through probability in the identified walks. If a random receiver i is two edges away from the sender j, the likelihood that i knows of j's price p_{jt} equals ω^2. Both potential buyers and non-buyers can equally forward price information they received from others, even while being outside the store. In a conducted pre-test, for different values of δ and ω we numerically determined the likelihood of $m_{ijt}(\delta, \omega) = 1$ describing that a randomly selected customer i receives the message sent by a likewise randomly selected distinct customer j. For the following experiments we chose $\delta = 6$ and $\omega \in \{0,\ 0.25,\ 0.4,\ 0.55,\ 1\}$ leading to rounded price transparencies 0%, 21%, 54%, 82%, and 100% respectively. Hereafter, these scenarios will be referred to as no price transparency (NT), low price transparency (LT), medium price transparency (MT), high price transparency (HT), and full price transparency (FT).

Numerical Analysis

For validating the plausibility of the model and the purpose of comparison, we define uniform pricing (UP) as our benchmark case where no price differentiation occurs. With UP there is only one group that includes all customers who are offered only one price ($G = 1, W = 1$). The profits generated by the evolution strategy for UP are depicted in Figure 1a/b/c and vary between 8264.41 and 9212.62. The standard error (SE) in all depicted UP scenarios ranged from 4.38 to 19.68. The graphs show that the loss aversion of the customers has no effect on the outcome since all customers are offered the same price. The price transparency, on the other hand, seems to have a solely positive impact on the profit. However, it can only accrue if there is a low visit frequency on the market ($\lambda = 20$). For higher visit frequencies there is no observable effect of the price transparency. In all examined UP scenarios the evolution strategy suggested setting approximately the same price. The mean of all offered prices was 94.3 with a standard deviation of 0.5. The prices slightly increased with the visit frequency (LF: 93.7, MF: 94.4, HF: 94.7).

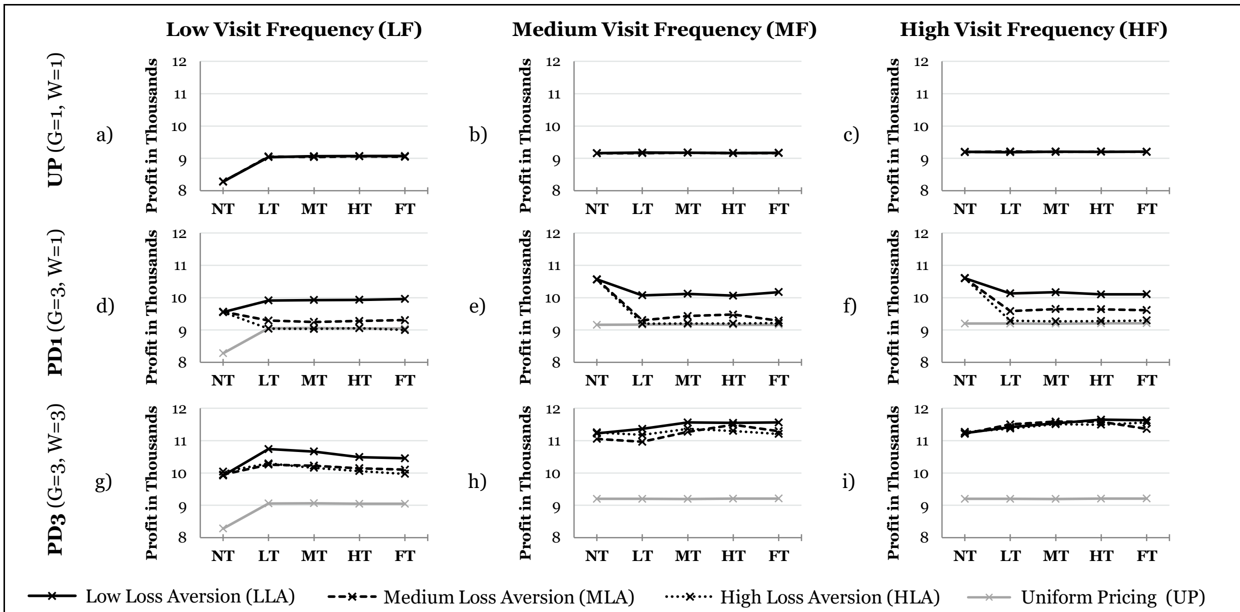

Figure 1. Profits for Uniform Pricing and Price Discrimination Strategies

To test the effects of differential pricing for each group g, we define different price discrimination (PD) strategies that differ in terms of available price subgroups $W \in \{1,\ 3\}$ that each group g's visitors are assigned to depending on their number of previous visits. These strategies will be called PD1 and PD3 respectively where the level of price individualisation increases with the number of available prices per group. Their profits are also depicted in Figure 1 for which the SE ranged from 4.39 to 20.82 and 2.34 and 82.90 respectively. The SE decreased with the visit frequency and was smaller for higher visit frequencies. PD1 can be described as a "one price per group" strategy which is equivalent to classical group pricing. As shown in Figure 1d/e/f, PD1 always outperforms UP significantly if there is no price transparency. The degree of loss aversion does not matter in this case since customers are only aware of their own prices. Price transparency has a solely positive impact on the profit in cases of low visit frequency and low loss aversion. In the other cases of PD1, the existence of price transparency leads to lower profit as compared to the no transparency case. The loss aversion seems to have a moderating influence. The higher the loss aversion is, the smaller is the generated profit and the more PD1 forfeits its superiority compared to UP under transparency. One possible explanation for this are the two opposing effects of WOM: with lower (higher) prices, more (less) customers are attracted to visiting the store but their willingness-to-pay decreases (increases). That means WOM may increase the profit by attracting customers to visit the store sooner than originally planned or more often. Simultaneously, customers may lower their willingness-to-pay if they observe lower prices of other customers on the market resulting in less profit. The higher the loss aversion of the customers is, the more pronounced is the latter negative effect of WOM. This explains why the profit-increasing effect in Figure 1d is only observable in the cases of low loss aversion, but not in the medium and high loss aversion scenarios where the negative effect outweighs the positive one because of the faster decreasing of the willingness-to-pay. In some cases of high loss aversion, the evolution strategy was able to find out that differential pricing in the form of PD1 is counter-productive and suggested offering the same price (≈94) to all groups equalling the UP strategy. The PD3 strategy provides three subgroups per group and thereby distinguishes between first-time and second-time returning customers. Figure 1g/h/i reveal that in comparison to PD1, the application of PD3 leads to greater profits and the price transparency does not result in a significant reduction of the profit. The profits generated in the no transparency case can mostly be maintained for higher transparency levels. Furthermore, the negative effects of the loss aversion seem to be lessened to the extent that even for highly loss aversive customers PD3 is able to outperform the UP strategy. The results also indicate that the influence of loss aversion on the profit gets lessened with increasing visit frequency which seems to counterbalance the impact of higher loss aversion. The experiments shown in Figure 1 were also re-conducted with the other solution methods with similar SE ranges. All methods suggested approximately the same prices for UP leading to the same profits. For PD1 all methods were able to find equivalent solutions for customers with low loss aversion except for simulated annealing which generated poorer results than UP in some price transparency cases. In the higher loss aversion cases of PD1, the other methods performed worse than the evolution strategy by suggesting solutions that fell below the UP curve generating profits close to 8.000. Similar observations were made for PD3 where the other methods lead to smaller profits particularly in the high loss aversion and low visit frequency scenarios as compared to the evolution strategy. Among the tested solution methods, the particle swarm optimisation was the closest to the evolution strategy in terms of generated profits.

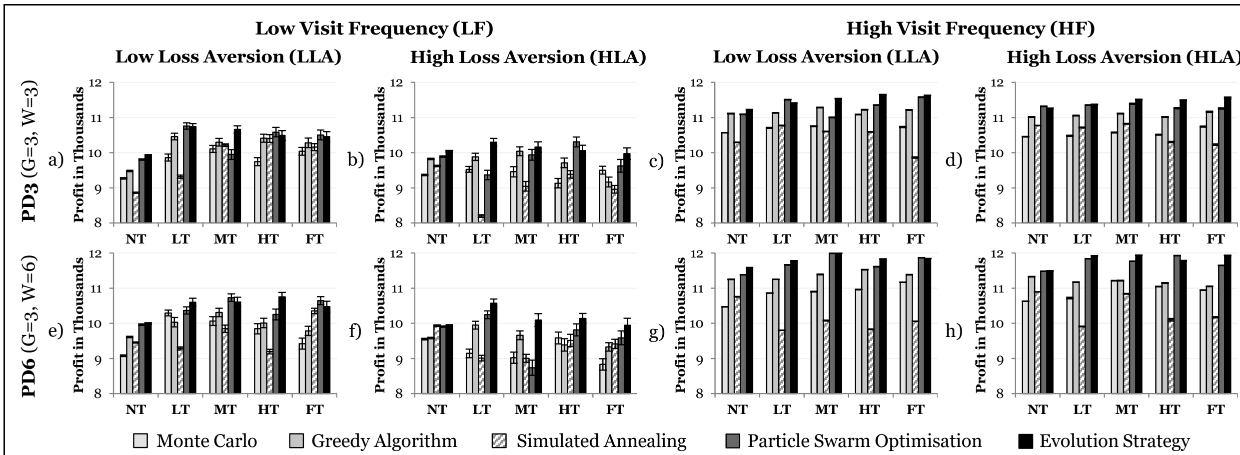

Figure 2. Benchmark of the Evolution Strategy Against Other Solution Methods

For determining the performance of the solution methods in a greater solution space, we tested them on a price discrimination strategy with $W = 6$ prices per group which we will refer to as PD6. The profits of PD3 and PD6 generated by the applied solution methods in selected scenarios are depicted in Figure 2 with their 95% confidence intervals. The SE ranged from 1.76 to 94.13 for PD3 and slightly increased for PD6 where it varied between 1.64 and 110.99. When the non-AI solution methods are compared to each other, it transpires that in most of the shown cases the greedy algorithm obtained significantly better results than the Monte Carlo simulation. This applies in particular to the high visit frequency cases. In most cases the greatest profits are generated either by the evolution strategy or the particle swarm optimisation. As the third AI solution method, simulated annealing performed significantly worse and in most cases generated even less profit than the non-AI methods suggesting that its optimisation approach does not suit the given problem structure. We tested the differences for statistical significance with a t-test (*, **, *** = $p < 0.05, p < 0.01, p < 0.001$ respectively, ns = not significant). In terms of generated profits with PD3, the evolution strategy was on average able to outperform the Monte Carlo simulation (+6.45%***), greedy algorithm (+3.40%**), simulated annealing (+10.55%***), and particle swarm optimisation (+1.16%^{ns}). The differences increased with PD6 in the greater solution space and the evolution strategy was able to consolidate its lead in particular over the Monte Carlo simulation (+8.29%***) and greedy algorithm (+5.42%***). Smaller difference changes were observed for simulated annealing (+11.58%***) and the particle swarm optimisation (+1.19%^{ns}).

	Case	**PD1**		**PD3**					**Case**	**PD1**		**PD3**				
	(LF)	**Profit**	**w = 1**	**Profit**		**w = 1**	**w = 2**	**w = 3**	**(HF)**	**Profit**	**w = 1**	**Profit**		**w = 1**	**w = 2**	**w = 3**
A	**LLA NT**	9536 (89.7)	186 (9.1)	9921 (90.2)	**SL**	193 (8.5)	189 (0.5)	144 (0.0)	**LLA NT**	10607 (98.2)	192 (9.9)	11231 (99.5)	**PU**	225 (0.0)	200 (7.9)	186 (2.0)
B			116 (18.0)		**SL**	125 (11.2)	119 (5.5)	116 (1.1)			119 (19.5)		**SL**	125 (12.2)	121 (5.2)	113 (2.6)
C			92 (62.6)		**SL**	99 (43.6)	86 (19.7)	86 (0.0)			93 (68.7)		**CY**	101 (32.9)	128 (0.0)	95 (36.6)
A	**LLA LT**	9893 (96.0)	149 (9.7)	10655 (94.4)	**CY**	174 (8.5)	220 (0.0)	125 (1.2)	**LLA LT**	10131 (96.6)	172 (8.6)	11417 (99.5)	**SL**	181 (9.4)	136 (0.6)	136 (0.0)
B			111 (19.2)		**SL**	123 (14.9)	113 (4.8)	113 (0.0)			112 (19.8)		**SL**	127 (9.7)	122 (7.5)	114 (2.8)
C			94 (67.2)		**PU**	129 (0.0)	104 (49.7)	96 (15.3)			94 (68.1)		**PU**	136 (0.0)	107 (40.0)	99 (29.5)
A	**LLA MT**	9951 (96.2)	149 (9.9)	10590 (93.1)	**SL**	185 (5.4)	155 (4.4)	155 (0.0)	**LLA MT**	10169 (97.0)	164 (9.2)	11537 (99.3)	**SL**	192 (9.1)	163 (0.9)	163 (0.0)
B			111 (19.1)		**CY**	122 (16.7)	166 (0.0)	102 (2.7)			114 (19.4)		**SL**	137 (0.5)	126 (14.0)	120 (5.4)
C			95 (67.2)		**PU**	131 (0.0)	105 (46.6)	97 (17.2)			94 (68.3)		**PU**	134 (0.0)	106 (40.7)	99 (28.7)
A	**LLA HT**	9933 (95.3)	149 (9.9)	10525 (90.4)	**CY**	190 (8.6)	237 (0.0)	170 (0.9)	**LLA HT**	10132 (96.3)	173 (8.5)	11660 (99.1)	**SL**	192 (9.4)	175 (0.6)	175 (0.0)
B			112 (19.0)		**PU**	162 (0.0)	127 (17.0)	105 (1.8)			114 (19.6)		**PU**	160 (0.0)	131 (13.8)	124 (6.1)
C			95 (66.4)		**PU**	135 (0.0)	109 (30.0)	98 (32.2)			94 (68.3)		**PU**	138 (0.0)	107 (40.6)	100 (28.6)
A	**LLA FT**	9992 (96.6)	150 (9.8)	10411 (89.8)	**CY**	184 (9.4)	205 (0.0)	178 (0.4)	**LLA FT**	10130 (96.7)	173 (8.4)	11614 (99.3)	**SL**	190 (9.7)	157 (0.3)	157 (0.0)
B			112 (19.2)		**SL**	137 (1.6)	128 (10.3)	119 (6.7)			113 (19.8)		**PU**	155 (0.0)	131 (11.7)	123 (8.2)
C			94 (67.6)		**PU**	136 (0.0)	110 (23.0)	98 (38.5)			94 (68.5)		**PU**	137 (0.0)	106 (42.9)	99 (26.6)
A	**HLA NT**	9559 (89.7)	190 (9.0)	10030 (90.4)	**SL**	198 (6.5)	190 (2.4)	186 (0.1)	**HLA NT**	10602 (97.9)	193 (9.8)	11275 (99.5)	**SL**	204 (3.0)	218 (0.0)	194 (6.9)
B			116 (18.0)		**SL**	122 (14.4)	114 (3.7)	82 (0.1)			118 (19.5)		**CY**	126 (9.6)	161 (0.0)	122 (10.2)
C			92 (62.7)		**SL**	98 (46.2)	92 (15.7)	83 (1.3)			93 (68.6)		**SL**	105 (16.0)	99 (31.3)	92 (22.5)
A	**HLA LT**	9057 (97.4)	94 (9.6)	10261 (91.0)	**SL**	192 (7.5)	115 (1.7)	115 (0.0)	**HLA LT**	9281 (93.3)	190 (4.9)	11373 (99.5)	**SL**	193 (8.9)	149 (0.8)	91 (0.3)
B			93 (19.9)		**PU**	175 (0.0)	127 (10.1)	109 (8.1)			96 (20.0)		**PU**	161 (0.0)	124 (17.4)	102 (2.6)
C			93 (67.9)		**PU**	242 (0.0)	108 (25.8)	98 (37.8)			94 (68.3)		**PU**	132 (0.0)	107 (33.1)	98 (36.4)
A	**HLA MT**	9038 (96.0)	94 (10.0)	10268 (89.9)	**CY**	193 (7.7)	256 (0.0)	162 (1.1)	**HLA MT**	9278 (92.2)	189 (5.0)	11506 (99.4)	**SL**	192 (8.6)	188 (0.3)	142 (1.1)
B			94 (19.7)		**PU**	259 (0.0)	128 (13.0)	118 (4.9)			99 (19.2)		**PU**	153 (0.0)	126 (16.5)	111 (3.5)
C			94 (66.3)		**PU**	188 (0.0)	106 (30.5)	96 (32.7)			95 (68.0)		**PU**	138 (0.0)	107 (40.6)	99 (28.8)
A	**HLA HT**	9063 (97.1)	93 (10.0)	10062 (88.0)	**SL**	187 (8.0)	169 (0.9)	169 (0.0)	**HLA HT**	9302 (91.8)	191 (5.0)	11512 (98.9)	**SL**	194 (8.3)	186 (1.4)	170 (0.4)
B			94 (19.6)		**PU**	217 (0.0)	130 (10.4)	118 (7.0)			100 (19.3)		**PU**	158 (0.0)	172 (0.0)	125 (19.8)
C			93 (67.5)		**PU**	184 (0.0)	106 (28.2)	97 (33.5)			95 (67.5)		**PU**	138 (0.0)	109 (26.0)	99 (43.1)
A	**HLA FT**	9010 (95.4)	95 (9.7)	10035 (88.9)	**SL**	181 (6.9)	146 (2.0)	119 (0.2)	**HLA FT**	9289 (92.1)	188 (5.0)	11547 (98.6)	**SL**	195 (7.9)	180 (1.4)	166 (0.5)
B			95 (19.6)		**PU**	227 (0.0)	127 (13.8)	103 (4.5)			100 (19.3)		**PU**	161 (0.0)	129 (14.3)	122 (5.5)
C			94 (66.1)		**PU**	141 (0.0)	108 (28.5)	96 (33.0)			95 (67.8)		**PU**	139 (0.0)	108 (32.1)	100 (36.9)

Table 2. Rounded Prices (Number of Sales) for Price Discrimination in Selected Scenarios

Table 2 shows the prices found by the evolution strategy in selected scenarios where low and high customer visit frequencies are compared in terms of low and high loss aversion. The average number of sales per price is given in parentheses. The profits increase from low to high visit frequency and decrease from low to high loss aversion, i.e. the highest profits can be expected in high visit frequency and low loss aversion scenarios. When PD1 is considered in scenarios of low visit frequency and high loss aversion, it should only be applied if there is no price transparency. If transparency exists in these scenarios, the deployment of PD1 is counter-productive and price discrimination should be entirely dispensed by the seller in favour of uniform pricing. In the other cases shown in Table 2 the application of PD1 can still be financially worthwhile even if WOM cannot be prevented. If price transparency exists in cases of low loss aversion, the offered prices to A customers should be lowered while the prices for B and C should remain fairly constant. This applies to both low and high visit frequency scenarios. A peculiarity can be seen for high visit frequency when low and high loss aversion scenarios are compared to each other. The prices of A customers are higher in the high loss aversion scenarios, while the prices of B and C are slightly reduced and remain constant respectively. This leads to a drop in sales for A customers, but keeps the number of B and C buyers at a high level. In the price structures of PD3 three different types of pricing schemes can be identified. *Successive Lowering* (SL) of prices is applied if the seller sets a high initial price to first serve customers with a high willingness-to-pay and then monotonically decreases the price to sell to those with a lower willingness-to-pay. In the *Pull Up* (PU) scheme the seller sets one or more initial price as high as to hinder visitors from buying the product at their first visits. The high price increases the customers' willingness-to-pay so that they can be charged higher prices on subsequent visits. The prices are successively lowered after the pulling up. The *Cyclic* (CY) scheme differs from the PU strategy in that it offers a high price intended to pull up the willingness-to-pay not on the first but on a later visit. It also presupposes that sales were realised by preceding prices. Table 2 reveals that for A customers the SL strategy should be applied in all high visit frequency cases except for one (LLA HT) where the PU strategy is suggested. In low visit frequency cases a mix of SL and CY is found to be optimal, where CY is suggested more often in low loss aversion scenarios. Price transparency seems to have only a small impact on the strategy type for A customers for whom in 75% of the cases SL is suggested. The situation is different for B customers where SL is mostly suggested only for relatively low levels of price transparency (NT or LT). For higher levels of price transparency, the PU strategy is recommended more frequently. For C customers the price transparency exhibits an even higher degree of separation precision in regard to selecting the correct strategy type. In NT scenarios SL should be adopted by the seller except for the HF LLA case where CY is suggested. In cases of price transparency, PU is applied without exception. To summarise, the impact of price transparency increases from A to C customers. If there is no price transparency, SL is the dominant type for all customers. If price transparency exists, the PU strategy is the most recommended type for B and C customers. The price structures shown in Table 2 also explain the aforementioned rather surprising result that a greater degree of price discrimination diminishes the effects of loss aversion. For this we compared the prices of PD1 and PD3 in the high visit frequency scenarios for highly loss aversive customers with medium price transparency (HF HLA MT). With the PD1 strategy only 50% of A customers buy the product at a relatively high price. The other half adapts their willingness-to-pay to a much lower level due to the lower prices of B and C customers and refuses to pay a significantly higher price. The deployment of PD3 increases the profit by 24.01% as compared to PD1. For accomplishing this, first A customers should be served by applying the SL scheme. In the meantime, B and C customers should be hindered from making a purchase by offering them high first-time visitor prices for two reasons: (1) their willingness-to-pay increases due to the PU strategy and (2) the willingness-to-pay of A customers does not decrease immediately as it is the case with PD1. A similar policy is suggested for the equivalent low visit frequency scenario (LF HLA MT).

Discussion

Conclusion

One of the most relevant and difficult decisions for firms is the adequate pricing of its products and services. In this context, Big Data opens up new opportunities for online stores (Bourreau et al. 2017). The more information a seller collects about her customers, the better she will be able to estimate their individual willingness-to-pay in order to offer them tailored prices. When offering individualised prices, WOM can have adverse consequences for the seller. Customers could feel disadvantaged if their peers pay less for the same product and react by lowering the willingness-to-pay. However, WOM may also have a favourable impact by attracting new customers. As an answer to our first research question RQ1 we introduced a pricing decision model for an online seller who has profound knowledge about the static and dynamic data of arriving customers. The static customer data constitutes the similarity between customers and the dynamic data is represented by their store visit history. Both types of information are used by the seller to assign visitors to customer groups that are served different prices. WOM was incorporated into our model for enabling buyers to share their prices with directly and indirectly connected other network participants. The objective function of the model consists of the maximisation of the seller's total profit depending on the prices to be offered. We investigated the performance of different pricing strategies that differed in their level of price individualisation. Our findings demonstrate that in many cases it is profitable to offer different prices to different customers. They also indicate that the negative influence of loss aversion can be neutralised by applying a pricing strategy with a higher degree of price discrimination which gives the seller more flexibility in adequately serving her customer base. Sometimes, it seems to be financially worthwhile to take the risk of customers lowering their willingness-to-pay. We answered our second research question RQ2 by applying an evolution strategy and comparing it to other AI and non-AI solution methods. Our results show that AI methods have the potential to generate greater profits for the considered problem structure. Their advantage over non-AI methods increases if pricing policies with a higher degree of price discrimination are deployed. However, our findings also indicate that not all AI methods are superior and should be thoroughly evaluated with regard to their suitability for solving the existing pricing decision problem, e.g. by testing more configurations for the optimisation approach.

Managerial Implications

Several managerial implications can be drawn from the examined scenarios in our study. Our results suggest that a pricing strategy with a higher degree of price discrimination performs best in all scenarios and should therefore be used preferably. But the higher the degree of price discrimination is, the more information about customers is required. If the collection and analysis of customer related information is limited (e.g. due to data protection by law), a firm might be compelled to use a strategy with a lower degree of price discrimination. In that case, firms should be cautious as price discrimination is not always beneficial and might lead to less profit as compared to UP. If firms have to some extent control over WOM, additional implications can be derived. If UP is applied by a firm, initiating WOM is only worthwhile if the visit frequency is low. For higher degrees of loss aversion and higher levels of visit frequency, WOM has mostly negative effects and should be avoided as much as possible. This is contrasted by the pricing strategies with a higher degree of price discrimination where WOM hardly changes the profits compared to the no transparency case. As demonstrated, in these cases WOM always benefits the firm by increasing the profits in all visit frequency scenarios. As regards setting prices, when the "one price per group" strategy (PD1) is applied in markets with low customer loss aversion, price transparency induces a price reduction for A customers, while the prices of B and C customers are hardly influenced and should remain close to their initial average willingness-to-pay. This strategy is found to be optimal regardless of the customer visit frequency. Only if the seller is confronted with highly loss aversive customers who visit the store less frequently, PD1 should not be applied as UP is superior when price transparency exists. Applying a pricing strategy with multiple prices per group (e.g. PD3) gives the seller more flexibility in serving her customers. The Successive Lowering (SL) pricing scheme with higher prices at first followed by their continuous lowering is mostly suggested for A customers regardless of the existing price transparency. The SL scheme is also the dominant strategy for C customers but only if there is no price transparency. As soon as price transparency exists, for C customers the Pull Up (PU) pricing scheme should be applied where high prices at initial visits increase the willingness-to-pay of customers by preventing them from purchasing the product. B customers should also be served with the PU scheme but only for high levels of price transparency. For lower levels, SL or the Cyclic (CY) pricing scheme are suggested where high prices are offered to returning visitors for increasing their willingness-to-pay.

Online stores may not always be able to accurately assess the characteristics of incoming customers. Erroneous assessments in this matter could lead to misjudgements of the customers' correct group membership. Thereby, each pricing decision involves the risk of mistakes by offering the wrong prices to the wrong customers. For instance, a customer with a low willingness-to-pay could be mistakenly assigned to the group of customers who usually exhibit a high willingness-to-pay and get offered too high prices. In order to disclose how a (partially) wrong customer classification would influence the outcome, with our current model we tested the effects of misclassification based on static customer attributes. We re-ran the profit calculation with the differential prices the evolution strategy had suggested for PD3. In the test, with a misjudgement probability of 5%, 10%, and 30%, the seller assigned customers not to their fitting group but to a random other group. On average, the profits of price discrimination were reduced by 3.22%**, 6.19%***, and 16.16%*** respectively. Although the profits decreased, differential pricing still performed significantly better than uniform pricing in the 5% and 10% misjudgement cases by 16.19%*** and 13.30%*** respectively. With a misjudgement probability of 30%, the generated profits exceeded uniform pricing's results slightly by 1.22%^{ns}. These results show that under a certain degree of uncertainty the profits are only marginally reduced und thereby indicate a robustness of the solutions against small to medium estimation errors. Only if customers are greatly misjudged in terms of group membership, the profits are substantially reduced but may still outperform the profits of uniform pricing.

Limitations and Future Research Directions

Our study aims to provide a conceptual basis for future research where the combined effects of different prices for different customers (price discrimination) and WOM are investigated more thoroughly. Because the study explores new frontiers in this field, some limitations need to be considered when assessing its numerical results. First, the model should be extended by incorporating a "general acceptance factor" for price discrimination depicting the probability by which differential pricing is either accepted or rejected by customers. More than 50% of customers would refrain from shopping on Amazon if they got to know of individualised prices that are based on their willingness-to-pay (Kalka and Krämer 2016). The model should also be extended by the price (un-)fairness that is perceived by customers and the emotional reaction upon observing a high degree of price discrimination on the market (i.e. greater values of G and W). By this, a pricing strategy with a greater degree of price discrimination may not always perform better since customer dissatisfaction leads to negative WOM (Xia et al. 2004) which in turn may result in fewer sales. Second, more constellations regarding customer behaviour should be tested to investigate how the results change and ascertain when the positive influence of higher degrees of price discrimination on neutralising loss aversion and enhancing word of mouth effects is reduced. The model should be extended in a way that the varied model parameters in our experiments (e.g. loss aversion) do not apply to all customers but vary among customers or segments. It is conceivable that in general customers with low purchasing power have a smaller willingness-to-pay and are more sensitive against disadvantageous price discrimination resulting in a faster decrease of their willingness-to-pay. Applied to our current experiments, this would probably evoke a more strict serving order for the customer groups A, B, and C. In order to prevent the negative effects of high loss aversion among C customers, at first A and thereafter B customers should be lead to making purchases by offering prices that are higher than the mean willingness-to-pay of C customers. Finally, in future investigations the importance of the correct assessment of customer characteristics should be examined in greater depth. The more diverse the customers are, the greater is the probability that they exhibit a different willingness-to-pay. This would justify a higher degree of customer separation leading to more customer groups and ultimately personalised pricing. In this respect, the impact of the estimation and classification errors on the profit could be amplified because the probability of offering the wrong price to the wrong customer would increase. This would lead price discrimination to lose its superiority at smaller estimation errors. Future research should therefore investigate when this point is reached for different constellations. It should also be investigated how the solution methods perform in optimising prices under uncertainty about customers, i.e. when customers are not correctly classified from the outset.

References

Aloysius, J., Deck, C., and Farmer, A. 2009. "Leveraging Revealed Preference Information by Sequentially Pricing Multiple Products," *Working Paper*.

Aydin, G., and Ziya, S. 2009. "Personalized Dynamic Pricing of Limited Inventories," *Operations Research* (57:6), pp. 1523-1531.

Bloch, F., and Quérou, N. 2013. "Pricing in social networks," *Games and Economic Behavior* (80), pp. 243-261.

Bonyadi, M. R., Michalewicz, Z., and Li, X.2014. "An analysis of the velocity updating rule of the particle swarm optimization algorithm," *Journal of Heuristics (20:4)*, pp. 417-452.

Bourreau, M., de Streel, A., and Graef, I. 2017. "*Big Data and Competition Policy: Market Power, Personalised Pricing and Advertising*," Centre on Regulation in Europe, Belgium.

Campbell, A. 2008. "Tell Your Friends! Word of Mouth and Percolation in Social Networks," *Massachusetts Institute of Technology. Job-Market Paper*.

Candogan, O., Bimpikis, K., and Ozdaglar, A. 2012. "Optimal pricing in networks with externalities," *Operations Research* (60:4), pp. 883-905.

Cannarella, C., and Piccioni, V. 2008. "Bad News Travels Faster: The Role of Word of Mouth in Innovation Propagation in Rural Areas," *The New Educational Review* (14:1), pp. 121-155.

Chang, W.-L., and Yuan, S.-T. 2007. "An overview of information goods pricing," *International Journal of Electronic Business* (5:3), pp. 294-314.

Chen, B., and Chen, J. 2017. "Compete in Price or Service?—A Study of Personalized Pricing and Money Back Guarantees," *Journal of Retailing* (93:2), pp. 154-171.

Chen, M., and Chen, Z.L. 2015. "Recent Developments in Dynamic Pricing Research: Multiple Products, Competition, and Limited Demand Information," *Production and Operations Management* (24:5), pp. 704-731.

Chen, Y. J., Zenou, Y., and Zhou, J. 2018. „Competitive pricing strategies in social networks." *The RAND Journal of Economics* (49:3), pp. 672-705.

Cowan, R., and Jonard, N. 2004. "Network structure and the diffusion of knowledge," *Journal of Economic Dynamics and Control* (28:8), pp. 1557-1575.

Dowsland, K. A., and Thompson, J. M. 2012. "Simulated Annealing," in *Handbook of Natural Computing*, Rozenberg, G., Bäck, T., and Kok, J. N. (eds.), Springer, pp. 1623-1655.

Emmerich, M., Shir, O. M., and Wang, H. 2018. "Evolution Strategies," in *Handbook of Heuristics*, Martí, R., Pardalos, P. M., and Resende, M. G. (eds.), Springer, pp. 1-31.

Enos, L. 2000. "*Amazon Apologizes for Pricing Blunder*," retrieved from https://www.ecommercetimes.com/story/4411.html. Accessed on 2019, May 1.

Fainmesser, I. P., and Galeotti, A. 2015. "Pricing network effects," *The Review of Economic Studies* (83), pp. 165-198.

Fibich, G., Gavious, A., and Lowengart, O. 2003. "Explicit solutions of optimization models and differential games with nonsmooth (asymmetric) reference-price effects," *Operations Research* (51:5), pp. 721-734.

Ghose, A., Mukhopadhyay, T., Rajan, U., and Choudhary, V. 2002. "Dynamic Pricing: A Strategic Advantage for Electronic Retailers," in *Proceedings of the 23rd International Conference on Information Systems*, pp. 304-315.

Gramstad, A. R. 2016. "Nonlinear pricing with local network effects," *Working Paper*.

Greenleaf, E. A. 1995. "The Impact of Reference Price Effects on the Profitability of Price Promotions". *Marketing Science* (14:1), pp. 82-104.

Grunert, K. G., Juhl, H. J., Esbjerg, L., Jensen, B. B., Bech-Larsen, T., Brunsø, K., and Øland Madsen, C. 2009. "Comparing methods for measuring consumer willingness to pay for a basic and an improved ready made soup product," *Food Quality and Preference* (20:8), pp. 607-619.

Hirsch, C. 2015. "*Amazon-Deutschland-Chef bestätigt unterschiedliche Preise*," retrieved from https://www.heise.de/newsticker/meldung/Amazon-Deutschland-Chef-bestaetigt-unterschiedliche-Preise-2866554.html. Accessed on 2019, May 1.

Hu, Z., Chen, X., and Hu, P. 2016. "Dynamic Pricing with Gain-Seeking Reference Price Effects," *Operations Research* (64:1), pp. 150-157.

Johnson, J. W., and Cui, A. P. 2013. "To influence or not to influence: External reference price strategies in pay-what-you-want pricing," *Journal of Business Research* (66:2), pp. 275-281.

Kahneman, D., and Tversky, A. 1979. "Prospect Theory: An Analysis of Decision under Risk," *Econometrica* (47:2), pp. 263-291.

Kalka, R., and Krämer, A. 2016. „Dynamic Pricing: Verspielt Amazon das Vertrauen seiner Kunden?," retreived from http://www.absatzwirtschaft.de/dynamic-pricing-verspielt-amazon-das-vertrauen-seiner-kunden-75271/. Accessed on 2019, May 1.

Kalyanaram, G., and Little, J. D. C. 1994. "An Empirical Analysis of Latitude of Price Acceptance in Consumer Package Goods," *Journal of Consumer Research,* (21:3), pp. 408-418.

Kamada, Y., and Öry, A. 2017. "Contracting with Word-of-Mouth Management," *Cowles Foundation Discussion Papers from Cowles Foundation for Research in Economics, Yale University*.

Kopalle, P. K., and Lindsey-Mullikin, J. 2003. "The impact of external reference price on consumer price expectations," *Journal of Retailing* (79:4), pp. 225-236.

Kopalle, P. K., Rao, A. G., and Assunção, J. L. 1996. "Asymmetric Reference Price Effects and Dynamic Pricing Policies," *Marketing Science* (15:1), pp. 60-85.

Koschate-Fischer, N., and Wüllner, K. 2017. "New developments in behavioral pricing research," *Journal of Business Economics* (87:6), pp. 809-875.

Krämer, A., Friesen, M., and Shelton, T. 2018. "Are airline passengers ready for personalized dynamic pricing? A study of German consumers," *Journal of Revenue and Pricing Management* (17:2), pp. 115-120.

Krishna, A., Briesch, R., Lehmann, D. R., and Yuan, H. 2002. "A Meta-analysis of the Impact of Price Presentation on Perceived Savings," *Journal of Retailing* (78:2), pp. 101-118.

Krishnamurthi, M., and Phillips, D. T. 1992. "An expert system framework for machine fault diagnosis," *Computers & Industrial Engineering* (22:1), pp. 67-84.

Krishnan, B. C., Dutta, S., and Jha, S. 2013. "Effectiveness of Exaggerated Advertised Reference Prices: The Role of Decision Time Pressure," *Journal of Retailing* (89:1), pp. 105-113.

Liu, Y., and Zhang, Z. J. 2006. "The Benefits of Personalized Pricing in a Channel," *Marketing Science* (25:1), pp. 97-105.

Mazumdar, T., Raj, S. P., and Sinha, I. 2005. “Reference Price Research: Review and Propositions,” *Journal of Marketing* (69:4), pp. 84-102.
McCarville, R. E., Crompton, J. L., and Sell, J. S. 1993. “The influence of outcome messages on reference prices,” *Leisure Science* (15:2), pp. 115-130.
Mochalova, A., and Nanopoulos, A. 2014. “Restricting the Spread of Firestorms in Social Networks,” in *Proceedings of the 22nd European Conference on Information Systems*, pp. 1-14.
Moon, S., Russell, G. J., and Duvvuri, S. D. 2006. “Profiling the reference price consumer,” *Journal of Retailing* (82:1), pp. 1-11.
Murthi, B. P. S., and Rao, R. C. 2012. "Price Awareness and Consumers’ Use of Deals in Brand Choice," *Journal of Retailing* (88:1), pp. 34-46.
Nasiry, J., and Popescu, I. 2011. "Dynamic Pricing with Loss-Averse Consumers and Peak-End Anchoring," *Operations Research (*59:6), pp. 1361-1368.
Niu, L., Yan, X.-W., Zhang, C.-Q., and Zhang, S.-C. 2002. "Product hierarchy-based customer profiles for electronic commerce recommendation," in *Proceedings of the 1st International Conference on Machine Learning and Cybernetrics* (2), pp. 1075-1080.
Nugroho, R., Zhao, W., Yang, J., Paris, C., Nepal, S., and Mei, Y. 2015. "Time-sensitive topic derivation in twitter," in *Proceedings of the 16th International Conference on Web Information Systems engineering*, pp. 138-152.
Onnela, J.-P., Saramäki, J., Hyvönen, J., Szabó, G., Lazer, D., Kaski, K., Kertész, J., and Barabàsi, A.-L. 2007. "Structure and tie strenghts in mobile communication networks," in *Proceedings of the National Academy of Science* (104:18), pp. 7332-7336.
Pfeffer, J., Zorbach, T., and Carley, K. M. 2014. "Understanding online firestorms: Negative word-of-mouth dynamics in social media networks," *Journal of Marketing Communications* (20:1-2), pp. 1-12.
Phlips, L. 1983. “The economics of price discrimination,” *Cambridge University Press*.
Pigou, A. C. 1920. *The Economics of Welfare*, London, Macmillan and Company.
Popescu, I., and Wu, Y. 2007. "Dynamic Pricing Strategies with Reference Effects," *Operations Research* (55:3), pp. 413-429.
Reibstein, D. J. 2002. "What attracts customers to online stores, and what keeps them coming back?" *Journal of the Academy of Marketing Science* (30:4), p. 465.
Richards, T. J., Liaukonyte, J., and Streletskaya, N. A. 2016. "Personalized pricing and price fairness," *International Journal of Industrial Organization* (44), pp. 138-153.
Schlereth, C., Eckert, C., and Skiera, B. 2012. "Using Discrete Choice Experiments to Estimate Willingsness to Pay Intervals," *Marketing Letters* (23:3), pp. 761-776.
Schmitz, S. W., and Latzer, M. 2002. "Competition in B2C e-Commerce: analytical issues and empirical evidence," *Electronic Markets* (12:3), pp. 163-174.
Shapiro, C., Carl, S., and Varian, H. R. 1998. “Information rules: a strategic guide to the network economy,” *Harvard Business Press*.
Shim, B., Choi, K., and Suh, Y. 2012. "CRM strategies for a small-sized online shopping mall based on association rules and sequential patterns," *Expert Systems with Applications* (39:9), pp. 7736-7742.
Thakur, S. S., Kundu, A., and Sing, J. K. 2011. "Bayesian Belief Networks–Based Product Prediction for E-Commerce Recommendation," in *Proceedings of the International Conference on Advances in Communication, Network, and Computing* (142), pp. 311-314.
Varian, H. 1989. "Price Discrimination," in *Handbook of Industrial Organization,* Schmalensee, R., and Willig, R. D. (eds.), Elsevier Science Publishers B.V., pp. 597-654.
Wang, Z. 2016. "Intertemporal Price Discrimination via Reference Price Effects," *Operations Research* (64:2), pp. 290-296.
Watts, D. H., and Strogatz, S. H. 1998. "Collective dynamics of ‘small-world’ networks," *Nature* (393:6684), pp. 440-442.
Wertenbroch, K., and Skiera, B. 2002. "Measuring consumers’ willingness to pay at the point of purchase," *Journal of Marketing Research* (39:2), pp. 228-241.
Winer, R. S. 1986. "A Reference Price Model of Brand Choice for Frequently Purchased Products," *Journal of Consumer Research* (13:2), pp. 250-256.
Xia, L., Monroe, K. B., and Cox, J. L. 2004. "The price is unfair! A conceptual framework of price fairness perceptions," *Journal of Marketing* (68:4), pp. 1-15.